IST 718: Big Data Analytics

UNIT 4-1 Spark Computing

Note: MATERIAL here is from a mix of Readings & sources as listed in References Slide(s)

01 Spark Computing

Apache Spark

Spark Components and Functionalities

Spark RDDs

Spark DataFrames

Spark Operations

Spark Mllib

Spark SQL

Spark and Hadoop

Hadoop is a **framework** for distributed processing and is comprised of YARN, MapReduce, HDFS and common modules.

Hadoop **ecosystem** adds to its capabilities: HBase, Storm, Mahout, Neo4j, Graph, etc.

With capabilities in file distribution, data security, resource management and DR, Hadoop is **a de facto standard** for Big Data.

MapReduce processing is **disk-based**, scaling by adding cheap computers and cheap disk.

Largest known cluster: Yahoo 42,000 nodes. Hadoop MapReduce uses **batch processing** and built ideally to crawl through web sites.

Spark is a **general-purpose** data processing engine that can run on its own or in Hadoop clusters through YARN.

Spark **capabilities** include SQL, streaming, machine learning and graph processing.

Spark is not a replacement for Hadoop but can provide an **alternative to Hadoop MapReduce** under several scenarios.

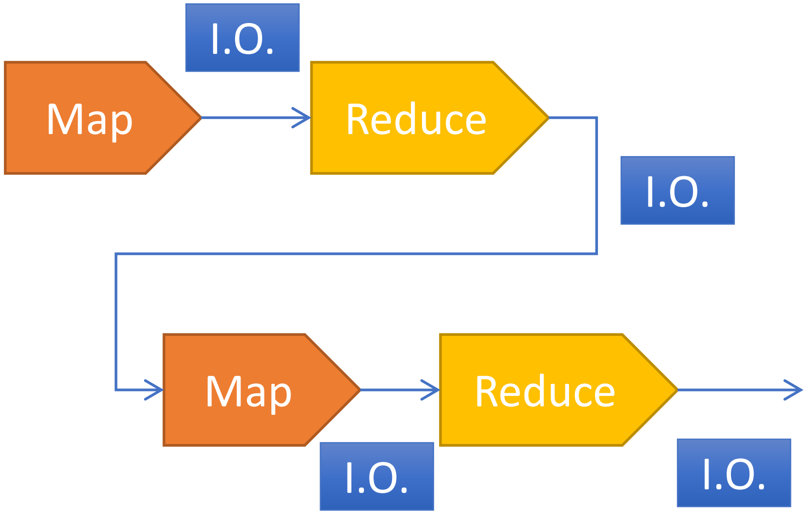
Spark provides rapid **in-memory** processing and scaling comes at a cost (memory).

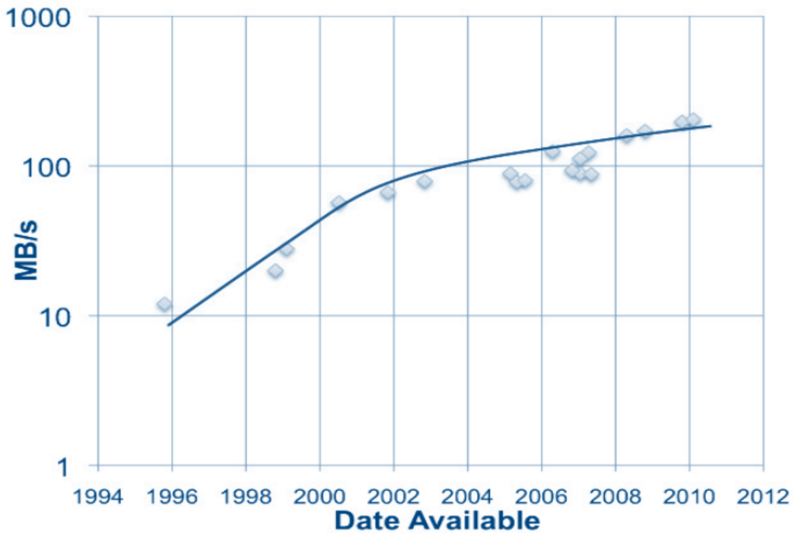
Largest know cluster: 8,000 nodes. Spark excels at **streaming** workloads, interactive queries, and machine-based learning.

Note: Hadoop and Spark can co-exist and is often the recommended solution for new implementations.

Hadoop

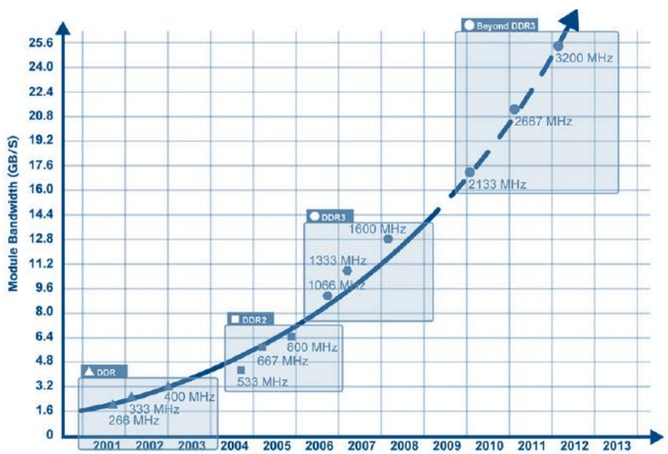
- Traditionally:
  - Hadoop uses single programming model: MapReduce
  - It only works with data on hard drives





Spark

- RAM bandwidth has been increasing exponentially
- Spark can perform in-memory computations



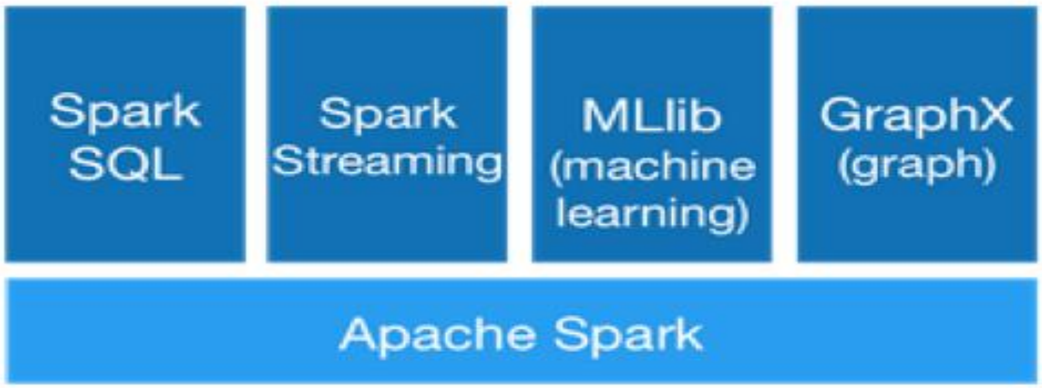
Bandwidths shown for 64-bit memory module. Date indicates approximate industry product introduction.

What is Spark?

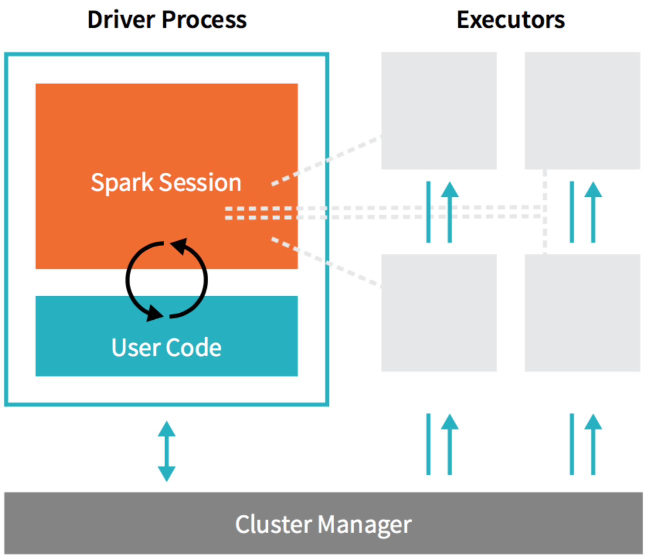
- ***Apache Spark*** is a fast, in-memory analytics system
- Spark has several high-level tools, including:
  - **ML**: a machine learning library
  - **Spark Streaming**: enables high-throughput, fault-tolerant stream processing of live data streams
  - **Spark SQL**: runs SQL and HiveQL queries
  - **GraphX**: an API for graphs and graph-parallel computation
- Spark can be executed in two ways:
  - Standalone
  - With a cluster manager such as YARN

Spark

"Apache Spark™ is a fast and general engine for large-scale data processing."



Spark Architectural Components



- Spark applications consist of a driver process and a set of executor processes.

Spark Driver Process

- The driver process runs the application’s “main” program
- Runs on one of the nodes in the cluster
- Is responsible for three things:
  - Maintaining information about the Spark applications
  - Responding to a user’s program or input
  - Analyzing, distributing, and scheduling work across the executors

Spark Executor Process

- Responsible for actually carrying out the work that the driver assigns to them.
- Each executor is responsible for two things:
  - Executing code assigned to it by the driver
  - Reporting the state of the computation on that executor back to the driver node

Cluster Manager

- Controls the physical machines
- Allocates resources to Spark applications
- Three Cluster Managers
  - Standalone
  - YARN
  - Mesos

Spark 1.6+ vs 2.0+

- Spark 1.6+ relied on transformations on arbitrary datasets known as Resilient Distributed Datasets (RDDs)
- Spark 2.0+ defines more structure in the form of DataFrames, which are similar to tables in SQL and data.frames in R
- The newest versions of Spark define DataSets which are statically-typed DataFrames (more structure)
- With more flexiblity comes greater power but less performance
- Future Spark machine learning will work with DataFrames and not RDD.

Classic Spark v. <2.0

The SparkContext

- The **SparkContext** object performs the following tasks:
  - It connects to the ResourceManager (like YARN) and asks for resources on the Hadoop cluster,
  - Starts executors on the worker nodes in the cluster that the ResourceManager allocated for the Spark application,
  - Sends the application code to the executors,
  - And finally, it sends tasks for the executors to run
- **SparkContext** is represented by the **sc** objec

Spark RDDs

- An RDD (resilient distributed dataset) is a fault-tolerant collection of elements on which operations can be performed in parallel.
- An RDD is an immutable collection that represents:
  - A dataset…
  - …broken up into a list of partitions
  - A list of dependencies on other RDDs
  - An optional list of preferred block locations for an HDFS file
  - Read-only

Important RDD Concepts

- Lineage
  - Information about how an RDD is derived from other datasets or other RDDs
  - RDD is not necessarily materialized all the time due to lazy execution
  - Lineage captured on disk as “lineage graph”
- Persistence
  - Indicate which RDDs which need to keep in memory for reuse
  - User can call “persist” method
- Partitioning
  - RDD elements can be partitioned across machines based on a key in each record

Sample RDD Lineage Graph

- r20 depends on many other RDDs
- See: https://jaceklaskowski.gitbooks.io/mastering-apache-spark/spark-rdd-lineage.html

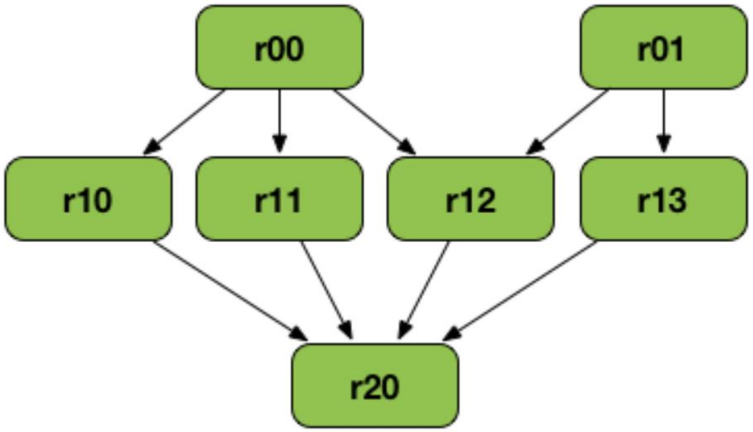


Figure 1. RDD lineage

Creating RDDs

- Can create an initial RDD by applying a transformation to data on disk
- Can create an initial RDD from a code object
- Example ways to create an RDD in Spark:
  - Use the parallelize operation to convert an existing code object into an RDD
  - Use textFile operation to convert a text file on HDFS into an RDD
  - Use sequenceFile operation to convert a binary file on HDFS into an RDD

Example: Creating RDDs

```
from pyspark import SparkContext
```

```
myarray = range(1,20)
myarray
```

```
[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19]
```

```
dist_array = sc.parallelize(myarray)
dist_array
```

```
ParallelCollectionRDD[0] at parallelize at PythonRDD.scala:223
```

RDD Persist

- Spark’s persist method
  - Indicate which RDDs to reuse
  - Indicate if you want to replicate across machines
  - Indicate priority of which in-memory data to spill to disk first
- Example

```
logsrdd = sc.textFile(“hdfs://user/mark/logdata”)
fatals = filter(lambda s: s.startswith(‘FATAL’), logsrdd)
fatals.cache()
fatals.count()
# Notes: logsrdd NOT loaded into RAM because of lazy evaluation
# fatals.cache() = rdd.persist(storageLevel.MEMORY) tries to
persist fatals rdd in memory
```

RDD Disk and Recover

- RDD can spill to disk
  - Degrade gracefully (to mapreduce performance)
  - Partitions not in use/lesser use and/or low priority spilled first
- Failure Recovery
  - Recovery is facilitated through redundant RDD block copies across cluster computers.
  - An RDD partition that fails is recovered by the Yarn/Spark Driver
  - Executer applies lineage to prior RDD (or original data on disk) to recover the RDD.

RDD Checkpointing

- Writes an RDD to disk to save the RDD in a specific state
- After checkpointing, future references the RDD don't need to perform upstream transformations in the lineage.
- Similar to caching except that the RDD is stored on disk instead of in memory.
- Example:

```
spark.sparkContext.setCheckpointDir("/some/path/
for/checkpointing")
words.checkpoint()
```

RDD Operations

- There are two types of operations that can be done on RDDs:
  - **Transformations**: create a new dataset/RDD from an existing one
  - **Actions**: Trigger a transformation and instructs spark to compute a result from a series of transformations.
- Transformations
  - lazy - they do not compute their results right away
- Actions
  - Instantiates the RDD
- See https://spark.apache.org/docs/latest/rdd-programming-guide.html#transformations for a list of transformations and actions.

RDD Dependencies and Transformations

- Dependency / transformation used synonymously in Spark the Definitive Guide text book
- Two Main Types of Dependencies / Transformation
  - Narrow – child partition depends on only one parent partition
    - E.g. map, filter, union
  - Wide – multiple child partitions depend on one parent partition
    - E.g. Join and group-by transformations
    - Materialize intermediate calculations on parent for fault recovery

Narrow Transformation / Dependency

- Each input partition contributes to one output partition
- See Spark the Definitive Guide, Figure 2.4
- Also called pipelining, spark tries to perform narrow operations in memory

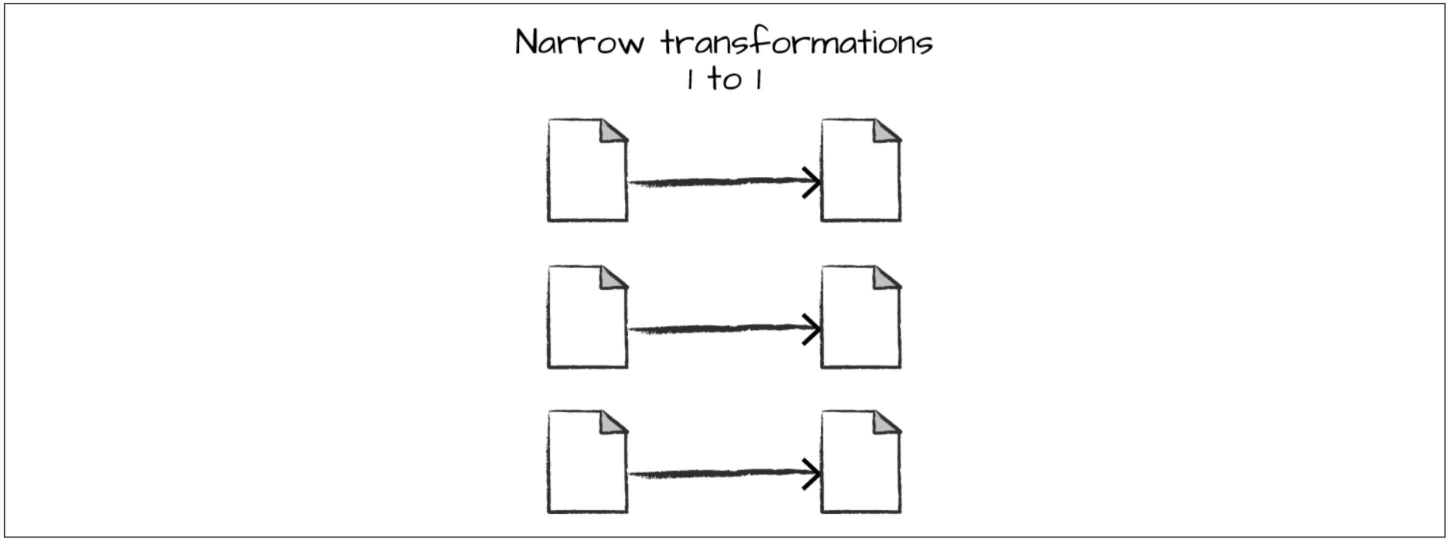


Figure 2-4. A narrow dependency

Wide Transformation / Dependency

- An input partition contributes to many output partitions
- See Spark the Definitive Guide, Figure 2.5
- Also called a shuffle where Spark exchanges partitions across the cluster

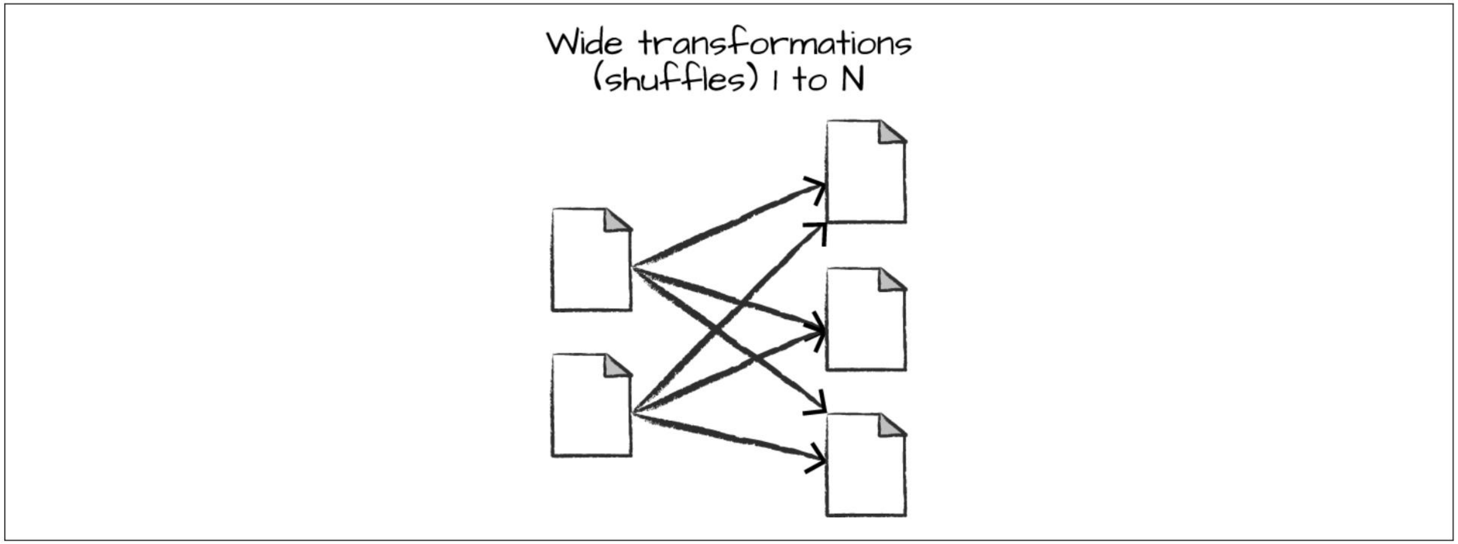


Figure 2-5. A wide dependency

Example Transformations

- **map(*func*):** returns a new distributed dataset formed by passing each element of the source through the function *func*.
- **flatMap(*func*):** same as **map** but when multiple key-value pairs are returned
- **filter(*func*):** return a new dataset formed by selecting those elements of the source on which *func* returns true.
- **reduceByKey(*func*):** when called on a dataset of (K, V) pairs, returns a dataset of (K, V) pairs where the values for each key are aggregated using the given reduce function *func*.
- **sortByKey([*ascending*],[*numTasks*]):** when called on a dataset of (K, V) pairs where K implements **Ordered**, returns a dataset of (K, V) pairs sorted by keys in ascending or descending order, as specified in the Boolean ***ascending*** argument.
- **join(*otherDataset*, [*numTasks*]):** when called on datasets of type (K, V) and (K, W), returns a dataset of (K, (V, W)) pairs with all pairs of elements for each key.
- **distinct([*numTasks*]):** returns a new dataset that contains the distinct elements of the source dataset.
- **pipe(*command*, [*envVars*]):** pipes each partition of the RDD through the provided shell *command*

Example: Transformations

```
neg_values = dist_array.map(lambda x : -1 * x)
neg_values.collect()
```

```
[-1,
 -2,
 -3,
 -4,
 -5,
 -6,
 -7,
 -8,
 -9,
 -10,
 -11,
 -12,
 -13,
 -14,
 -15,
 -16,
 -17,
 -18,
 -19]
```

```
large_values = dist_array.filter(lambda y: y > 10)
large_values.collect()
```

```
[11, 12, 13, 14, 15, 16, 17, 18, 19]
```

Example Actions

- **reduce(*func*):** Aggregate the elements of the dataset using a function func (which takes two arguments and returns one). The function should be commutative and associative so that it can be computed correctly in parallel.
- **foreach(*func*):** Runs the function *func* on each element in the dataset.
- **count():** returns the number of elements in the dataset.
- **first():** returns the first element in the dataset.
- **take(*n*):** returns an array with the first ***n*** elements of the dataset.
- **saveAsTextFile(*path*):** writes the elements in the dataset out to a file in HDFS (or some other file system).
- **saveAsSequenceFile(*path*):** writes the elements to HDFS in the **SequenceFile** format.

Example: Actions

```
large_values = dist_array.filter(lambda y: y > 10)
large_values.collect()
```

```
[11, 12, 13, 14, 15, 16, 17, 18, 19]
```

```
large_values.count()
```

```
9
```

```
large_values.reduce(lambda x,y : x+y)
```

```
135
```

WordCount in Spark (1 of 2)

```
constitution = sc.textFile("/user/root/constitution.txt")

wordCounts = constitution.flatMap(lambda line: line.split())
         .map(lambda word: (word, 1))
         .reduceByKey(lambda a, b: a+b)
```

```
wordCounts.take(10)
```

```
[(u'all', 37),
 (u'Jr.,', 1),
 (u'Legislatures', 3),
 (u'Roads;', 1),
 (u'bear', 2),
 (u'needful', 2),
 (u'Place', 3),
 (u'four', 2),
 (u'race,', 1),
 (u'Department', 1)]
```

WordCount in Spark (2 of 2)

```
swapped_wordCounts = wordCounts.map(lambda record : (record[1], record[0]))
sorted_counts = swapped_wordCounts.sortByKey(ascending = False)
sorted_counts.take(20)
```

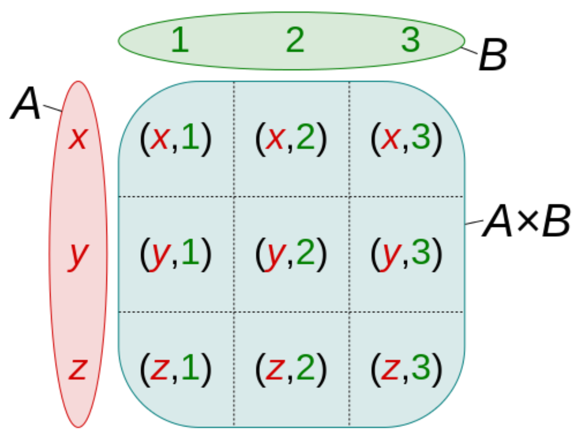
```
[(662, u'the'),
 (493, u'of'),
 (293, u'shall'),
 (256, u'and'),
 (183, u'to'),
 (178, u'be'),
 (157, u'or'),
 (137, u'in'),
 (100, u'by'),
 (94, u'a'),
 (85, u'United'),
 (81, u'for'),
 (79, u'any'),
 (72, u'President'),
 (64, u'The'),
 (64, u'as'),
 (63, u'have'),
 (55, u'States,'),
 (52, u'such'),
 (47, u'State')]
```

Operations on key-value pair RDDs

- Operations on key-value pair datasets are at the foundation of Hadoop, MapReduce, and Spark 1.6
  - **groupByKey()**: group values with the same key, ex. rdd.groupByKey()
  - **mapValues(f)**: applies function only to values not keys
  - **flatMapValues(f):** same as mapValues when function returns several values
  - **keys():** Returns RDD with only the keys
  - **values():** Returns RDD with only the values
- Simple operations on RDDs:
  - **union(otherRDD)**: makes the union of all key-value pairs

Join operations on pairs of key-value pair RDDs: join operations

- Joins are a fundamental operation of data which compute the **Cartesian product** between two sets (e.g., two RDDs)
$$A \times B = \{(a, b) \mid a \in A \text{ and } b \in B\}$$
- Most of the time, joins are paired with a filter to improve performance



Join operations on pairs of key-value pair RDDs: join operations

- We can use this idea to *join* key-value pairs and then filter for pairs that have the same key
- RDD join performs an “inner join”
- Inner Join: Keys must be present in the left and right hand RDD.

```
A = sc.parallelize([
  [1,1],
  [1,2],
  [2,3]]
)
B = sc.parallelize([
  [1, "A"],
  [2, "B"]
])
```

```
A.join(B).collect()
```

```
[(1, (1, 'A')), (1, (2, 'A')), (2, (3, 'B'))]
```

Join operations on pairs of key-value pair RDDs

- Lets suppose we want to compute the total number of orders per state using:
  - Locations: locationID, state
  - Transactions: transactionID, locationID, number of orders
- Activity: how can we use join to achieve this?
- Explore leftOuterJoin and rightOuterJoin

```
locations = sc.parallelize([
  ['loc1', 'NY'],
  ['loc2', 'NY'],
  ['loc3', 'PA'],
  ['loc4', 'FL']
])
transactions = sc.parallelize([
  [1, 'loc1', 2.],
  [2, 'loc1', 3.],
  [3, 'loc2', 5.],
  [4, 'loc5', 5.]
])
```

Spark 2.0

DataFrames

DataFrames

- The problem with RDDs is that they do not have enough structure
- They are harder to optimize and therefore slow
- DataFrames tries to solve this by adding structure
- A DataFrame is a distributed collection of data organized into named columns
- Similar to Pandas DataFrames but distributed across the cluster
- You access the Spark 2.0+ functionality using the **spark** object

DataFrames (2)

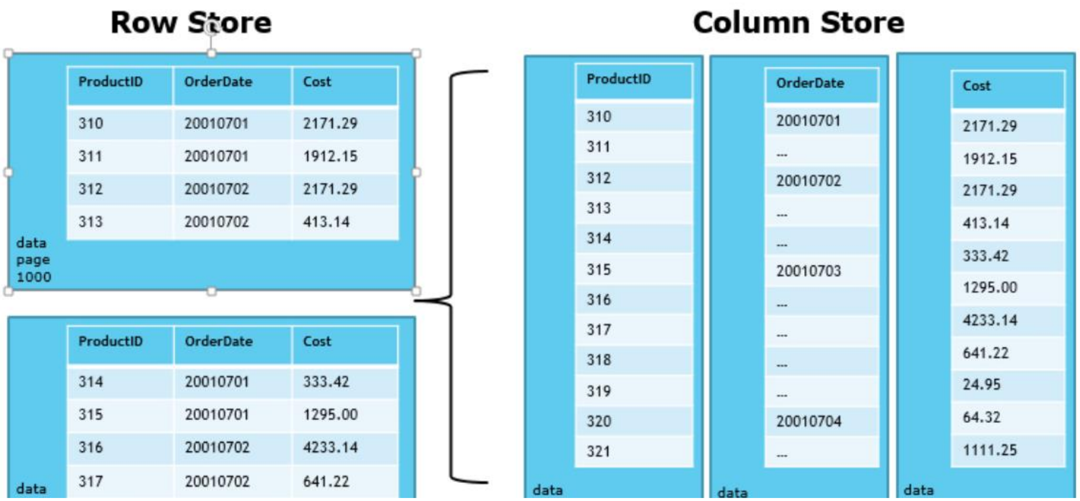
- You can read from multiple sources into dataframes

and more ...

Formats and Sources supported by DataFrames

DataFrames (3)

- One preferred source is Parquet files
- Parquet files are datasets stored in columns



DataFrame operations

- Creation of dataframes:
  - From Row objects:

```python
from pyspark.sql import Row
raw_data = [Row(state='NY', month='JAN', orders=3),
            Row(state='NJ', month='JAN', orders=4),
            Row(state='NY', month='FEB', orders=5),
           ]
data_df = spark.createDataFrame(raw_data)
```

  - From RDDs:

```python
example_rdd_with_rows.toDF()
```

  - From files:

```python
farmers_markets = spark.read.csv('/databricks-datasets/data.gov/farmers_markets_geographic_data/data-001/market_data.csv',
                                 header=True,
                                 inferSchema=True)
```

```python
spark.read.parquet(filepath)
```

DataFrame operations

- All data in a specific column has the same type
- DataFrame types can be hierarchical: The type of a column might be another "DataFrame"
- **You cannot perform dataframe operations using Python**
- Instead, you transform DataFrames by **selecting**, **modifying**, **filtering**, **joining**, **grouping**, or **aggregating** using specialized Spark commands similar to SQL
- Many of these commands are **symbolic representations** of the operations
- After the transformations, Spark builds an *execution plan* that is optimized for the column types and the operations

Exploring a DataFrame

- **printSchema():** shows the datatypes of the dataframe
- **show()**: prints the first *n* rows
- **take():** return first *n* rows
- **sample(withReplacement, fraction):** randomly sample rows (approximate)
- **display(df):** (only in DataBricks) exploratory interface for dataframe

Selecting and modifying a DataFrame

- **select(*expressions):** returns a new DataFrame with columns
- **withColumn(colName, expression):** creates a new column based on the expression
- Expressions are **symbolic operations**
- Symbolic operations can hold *literal* values and *placeholders* for column names
- You can perform symbolic operations on both literals and placeholders
- Some symbolic operations are available in pyspark.sql.functions

Symbolic operations

- expression = 1 + n_employees
- To express the previous operation, I need a *literal* value (1) and a *placeholder* for the column n_employees

```
1 + fn.col('n_employees')
```

```
t[23]: Column<(n_employees + 1)>
```

- A symbolic operation produces a *column object which contains the defined operations*

Symbolic operations

```
locations_df.select(1 + fn.col('n_employees')).show(10)
```

▸ (3) Spark Jobs

```
+-----------------+
|(n_employees + 1)|
+-----------------+
|                4|
|                9|
|                4|
|                2|
+-----------------+
```

Change column name

```
new_column = 1 + fn.col('n_employees')
locations_df.select(new_column.alias('new_column')).show(10)
```

▸ (3) Spark Jobs

```
+----------+
|new_column|
+----------+
|         4|
|         9|
|         4|
|         2|
+----------+
```

Change column type

```
locations_df.\
  select(new_column.alias('new_column').cast('float')).\
  show(10)
```

▸ (3) Spark Jobs

```
+----------+
|new_column|
+----------+
|       4.0|
|       9.0|
|       4.0|
|       2.0|
+----------+
```

Selecting and modifying (1)

- You can use select to select columns, modify them, or create new columns

```
locations_df.show(10)
```

▸ (3) Spark Jobs

```
+-----------+-----------+-----+
|location_id|n_employees|state|
+-----------+-----------+-----+
|       loc1|          3|   NY|
|       loc2|          8|   NY|
|       loc3|          3|   PA|
|       loc4|          1|   FL|
+-----------+-----------+-----+
```

```
locations_df.\
  select('n_employees',
         'location_id',
         'state',
         (fn.col('n_employees') + 1).alias('n_employees_plus_1'),
         (fn.col('n_employees') > 5).alias('more_than_5_empl')
        ).\
  show(10)
```

▸ (3) Spark Jobs

```
+-----------+-----------+-----+------------------+----------------+
|n_employees|location_id|state|n_employees_plus_1|more_than_5_empl|
+-----------+-----------+-----+------------------+----------------+
|          3|       loc1|   NY|                 4|           false|
|          8|       loc2|   NY|                 9|            true|
|          3|       loc3|   PA|                 4|           false|
|          1|       loc4|   FL|                 2|           false|
+-----------+-----------+-----+------------------+----------------+
```

Selecting and modifying (2)

- The following code snippet in that new columns are created using utility functions provided by the Spark SQL utility function (fn) module.
- Note that fn.lit() is needed to create a literal passed to pow

```
locations_df.\
  select(fn.sqrt('n_employees'),
         'n_employees',
         fn.pow(fn.col('n_employees'),
                fn.lit(2))).\
  show()
```

▸ (3) Spark Jobs

```
+------------------+-----------+--------------------+
| SQRT(n_employees)|n_employees|POWER(n_employees, 2)|
+------------------+-----------+--------------------+
|1.7320508075688772|          3|                 9.0|
|2.8284271247461903|          8|                64.0|
|1.7320508075688772|          3|                 9.0|
|               1.0|          1|                 1.0|
+------------------+-----------+--------------------+
```

Filtering

- **where(expression)**: select only rows where expression is true
- Expressions can be complex:

```
locations_df.where((fn.col('n_employees') > 2) & (fn.col('state') == 'PA')).show()
```

▸ (3) Spark Jobs

```
+-----------+-----------+-----+
|location_id|n_employees|state|
+-----------+-----------+-----+
|       loc3|          3|   PA|
+-----------+-----------+-----+
```

Joining

- **Inner joins** (keep rows with keys that exist in the left and right datasets)
- **Outer joins** (keep rows with keys in either the left or right datasets)
- **Left outer joins** (keep rows with keys in the left dataset)
- **Right outer joins** (keep rows with keys in the right dataset)
- Left semi joins (keep the rows in the left, and only the left, dataset where the key appears in the right dataset)
- Left anti joins (keep the rows in the left, and only the left, dataset where they do not appear in the right dataset)
- Natural joins (perform a join by implicitly matching the columns between the two datasets with the same names)
- Cross (or Cartesian) joins (match every row in the left dataset with every row in the right dataset)

Inner Join

- Keep rows with keys that exist in left and right data frames

```
locations_df.join(transactions_df, on='location_id').show()
```

▸ (5) Spark Jobs

```
+-----------+-----------+-----+--------+--------------+
|location_id|n_employees|state|n_orders|transaction_id|
+-----------+-----------+-----+--------+--------------+
|       loc1|          3|   NY|     2.0|             1|
|       loc1|          3|   NY|     3.0|             2|
|       loc3|          3|   PA|     5.0|             3|
+-----------+-----------+-----+--------+--------------+
```

```
locations_df.show(10)
```

▸ (3) Spark Jobs

```
+-----------+-----------+-----+
|location_id|n_employees|state|
+-----------+-----------+-----+
|       loc1|          3|   NY|
|       loc2|          8|   NY|
|       loc3|          3|   PA|
|       loc4|          1|   FL|
+-----------+-----------+-----+
```

```
transactions_df.show(10)
```

▸ (3) Spark Jobs

```
+-----------+--------+--------------+
|location_id|n_orders|transaction_id|
+-----------+--------+--------------+
|       loc1|     2.0|             1|
|       loc1|     3.0|             2|
|       loc3|     5.0|             3|
|       loc5|     5.0|             4|
+-----------+--------+--------------+
```

Left outer join

- Keep rows with keys that exist in left data frame

```
locations_df.join(transactions_df, on='location_id', how='left').show()
```

▸ (5) Spark Jobs

```
+-----------+-----------+-----+--------+--------------+
|location_id|n_employees|state|n_orders|transaction_id|
+-----------+-----------+-----+--------+--------------+
|       loc1|          3|   NY|     2.0|             1|
|       loc1|          3|   NY|     3.0|             2|
|       loc3|          3|   PA|     5.0|             3|
|       loc2|          8|   NY|    null|          null|
|       loc4|          1|   FL|    null|          null|
+-----------+-----------+-----+--------+--------------+
```

```
locations_df.show(10)
```

▸ (3) Spark Jobs

```
+-----------+-----------+-----+
|location_id|n_employees|state|
+-----------+-----------+-----+
|       loc1|          3|   NY|
|       loc2|          8|   NY|
|       loc3|          3|   PA|
|       loc4|          1|   FL|
+-----------+-----------+-----+
```

```
transactions_df.show(10)
```

▸ (3) Spark Jobs

```
+-----------+--------+--------------+
|location_id|n_orders|transaction_id|
+-----------+--------+--------------+
|       loc1|     2.0|             1|
|       loc1|     3.0|             2|
|       loc3|     5.0|             3|
|       loc5|     5.0|             4|
+-----------+--------+--------------+
```

Right outer join

- Keep rows with keys that exist in right data frame

```
locations_df.join(transactions_df, on='location_id', how='right').show()
```

▸ (5) Spark Jobs

```
+-----------+-----------+-----+--------+--------------+
|location_id|n_employees|state|n_orders|transaction_id|
+-----------+-----------+-----+--------+--------------+
|       loc1|          3|   NY|     2.0|             1|
|       loc1|          3|   NY|     3.0|             2|
|       loc3|          3|   PA|     5.0|             3|
|       loc5|       null| null|     5.0|             4|
+-----------+-----------+-----+--------+--------------+
```

```
locations_df.show(10)
```

▸ (3) Spark Jobs

```
+-----------+-----------+-----+
|location_id|n_employees|state|
+-----------+-----------+-----+
|       loc1|          3|   NY|
|       loc2|          8|   NY|
|       loc3|          3|   PA|
|       loc4|          1|   FL|
+-----------+-----------+-----+
```

```
transactions_df.show(10)
```

▸ (3) Spark Jobs

```
+-----------+--------+--------------+
|location_id|n_orders|transaction_id|
+-----------+--------+--------------+
|       loc1|     2.0|             1|
|       loc1|     3.0|             2|
|       loc3|     5.0|             3|
|       loc5|     5.0|             4|
+-----------+--------+--------------+
```

Outer join

- Keep rows with keys that exist in either the left or right data frames

```
1  locations_df.join(transactions_df, on='location_id', how='outer').show()
```

▸ (5) Spark Jobs

```
+-----------+-----------+-----+--------+--------------+
|location_id|n_employees|state|n_orders|transaction_id|
+-----------+-----------+-----+--------+--------------+
|       loc1|          3|   NY|     2.0|             1|
|       loc1|          3|   NY|     3.0|             2|
|       loc3|          3|   PA|     5.0|             3|
|       loc2|          8|   NY|    null|          null|
|       loc4|          1|   FL|    null|          null|
|       loc5|       null| null|     5.0|             4|
+-----------+-----------+-----+--------+--------------+
```

```
1  locations_df.show(10)
```

▸ (3) Spark Jobs

```
+-----------+-----------+-----+
|location_id|n_employees|state|
+-----------+-----------+-----+
|       loc1|          3|   NY|
|       loc2|          8|   NY|
|       loc3|          3|   PA|
|       loc4|          1|   FL|
+-----------+-----------+-----+
```

```
1  transactions_df.show(10)
```

▸ (3) Spark Jobs

```
+-----------+--------+--------------+
|location_id|n_orders|transaction_id|
+-----------+--------+--------------+
|       loc1|     2.0|             1|
|       loc1|     3.0|             2|
|       loc3|     5.0|             3|
|       loc5|     5.0|             4|
+-----------+--------+--------------+
```

Grouping

- **groupBy(*expressions)**: groups by a list of expressions
- Typically, a list of columns:

```
locations_df.\
  join(transactions_df, on='location_id').\
  groupBy('state')
```

```
Out[76]: <pyspark.sql.group.GroupedData at 0x7f4ac607ee50>
```

- Note that this transformation not do anything until we perform an action on the group object like an aggregate action.

Aggregate

- There are some special functions that only work on grouped data
- They are applied using the method **agg(*expressions)**
- For example:
  - fn.sum, fn.stddev: self explanatory
  - fn.count: counts when column is not null
  - fn.countDistinct: how many distinct values of a column

Aggregate

```
locations_df.\
  join(transactions_df, on ='location_id').\
  groupBy('state').\
  agg(fn.sum('n_orders')).\
  show()
```

▸ (5) Spark Jobs

```
+-----+-------------+
|state|sum(n_orders)|
+-----+-------------+
|   PA|          5.0|
|   NY|          5.0|
+-----+-------------+
```

Spark ML

- Spark ML implements several machine learning algorithms at scale:
  - Regression
  - Classification
  - Decision Trees
  - Clustering
- It works on Spark DataFrames by performing transformations of the data
- A typical data science analysis requires several transformations
- These transformations can be implemented through Pipelines

Spark ML (2)

- A model is known as **Estimator** in Spark ML and the typical cycle for such objects is as follows
  1. Define zero or more **input columns**
  2. Define zero or more **output columns**
  3. Define **parameters** of the estimator
  4. **Fit** the estimator, which returns a **fitted model**
  5. Use the fitted model to perform **transformations**

Example Spark machine learning workflow

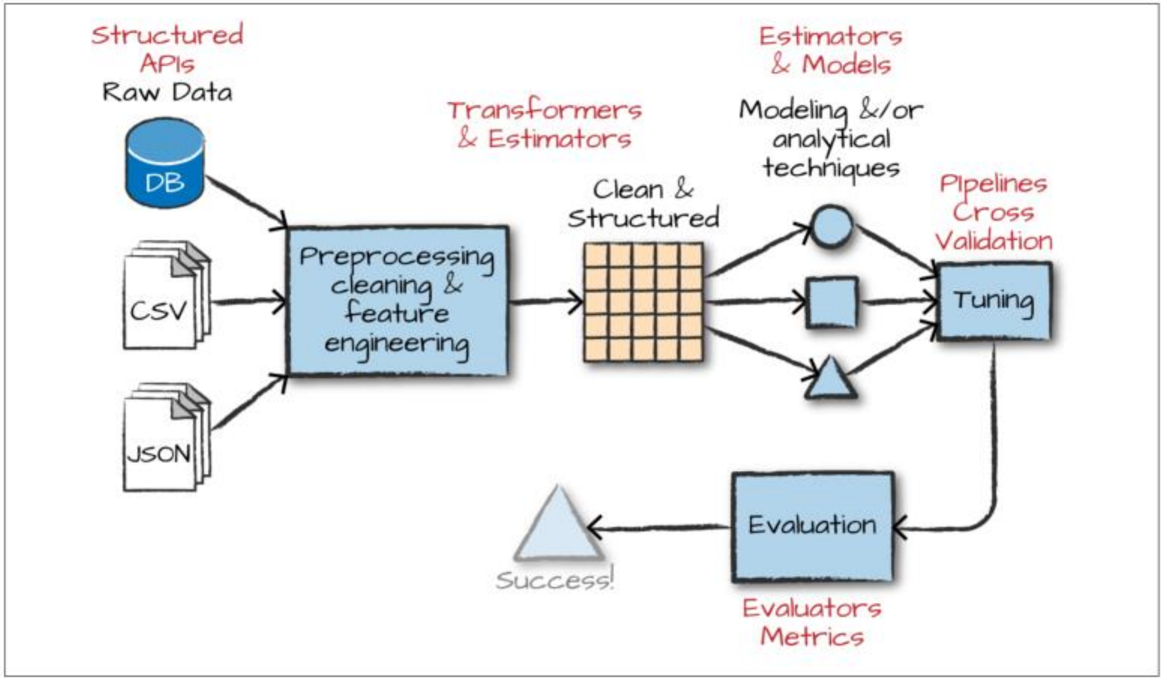


Figure 24-2. The machine learning workflow, in Spark

Spark ML: Transformers and Estimators

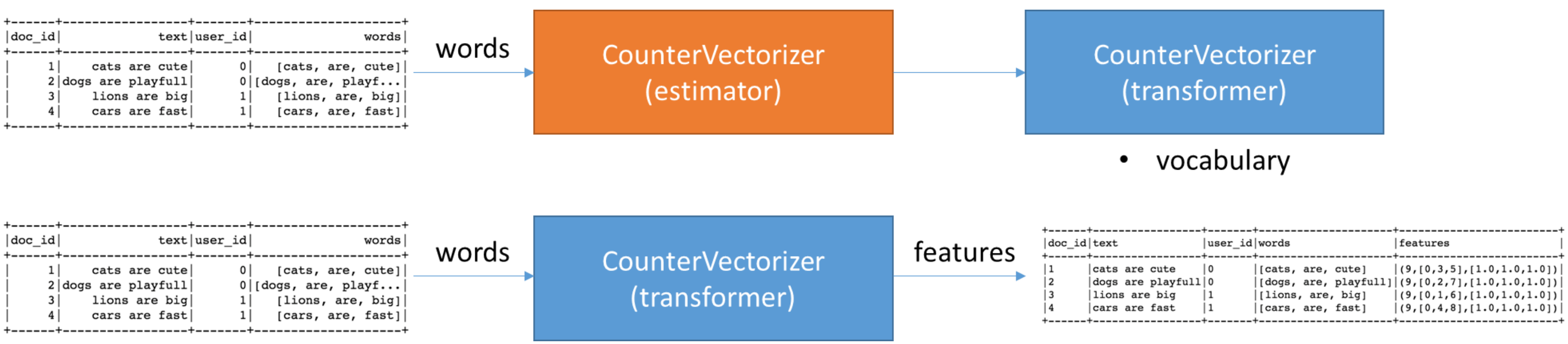
- Note that Spark ML for RDD is getting deprecated
- Preferred method in the future is to work only with DataFrames.
- Spark Machine Learning works by creating transformers and estimators DataFrames as inputs

doc_id	text	user_id
1	cats are cute	0
2	dogs are playfull	0
3	lions are big	1
4	cars are fast	1

doc_id	text	user_id	words
1	cats are cute	0	[cats, are, cute]
2	dogs are playfull	0	[dogs, are, playf...
3	lions are big	1	[lions, are, big]
4	cars are fast	1	[cars, are, fast]

Spark ML: Transformers and Estimators

- **Transformers** convert raw data in some way
- **Estimators** need to learn something from the data in order to transform the data
- For example, if we want to count terms in text, we need to know how many terms are in all documents



Example Spark Transformer

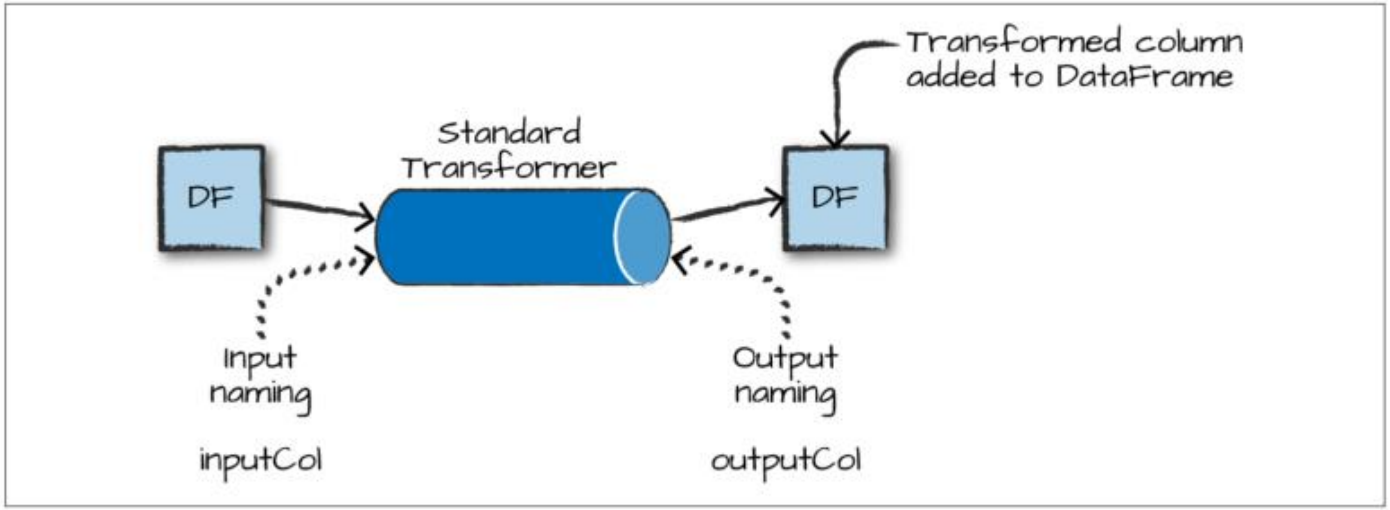
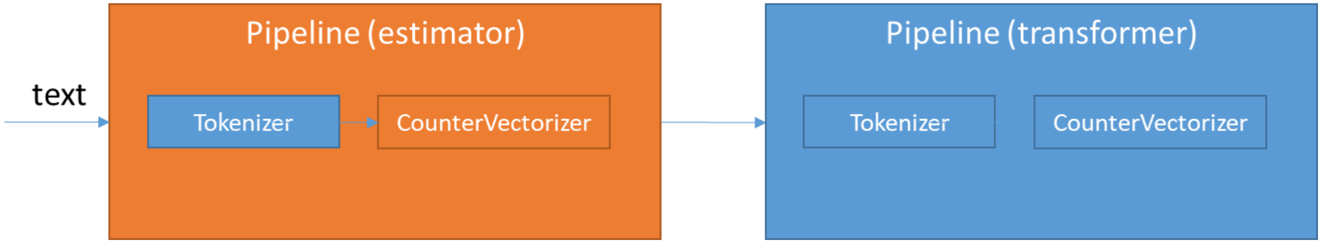


Figure 24-3. A standard transformer

Spark ML: Pipelines

- Data science is all about building data analytic pipelines from raw data to models
- Spark ML Pipeline chains multiple Transformers and Estimators
- Pipelines can be saved and shared
- A Pipeline always starts as an Estimator that needs to be fitted

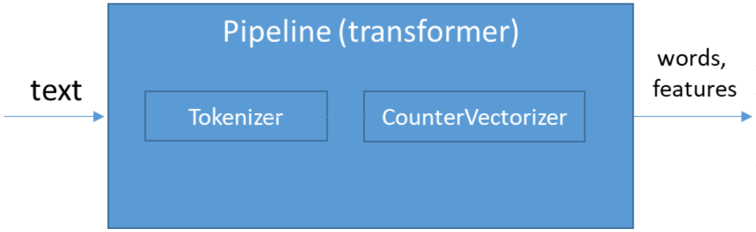
doc_id	text	user_id
1	cats are cute	0
2	dogs are playfull	0
3	lions are big	1
4	cars are fast	1



Spark ML: Pipelines

- A Pipeline **always** needs to be fitted even when stages are all transformers
- A Pipeline transformer contains an entire process

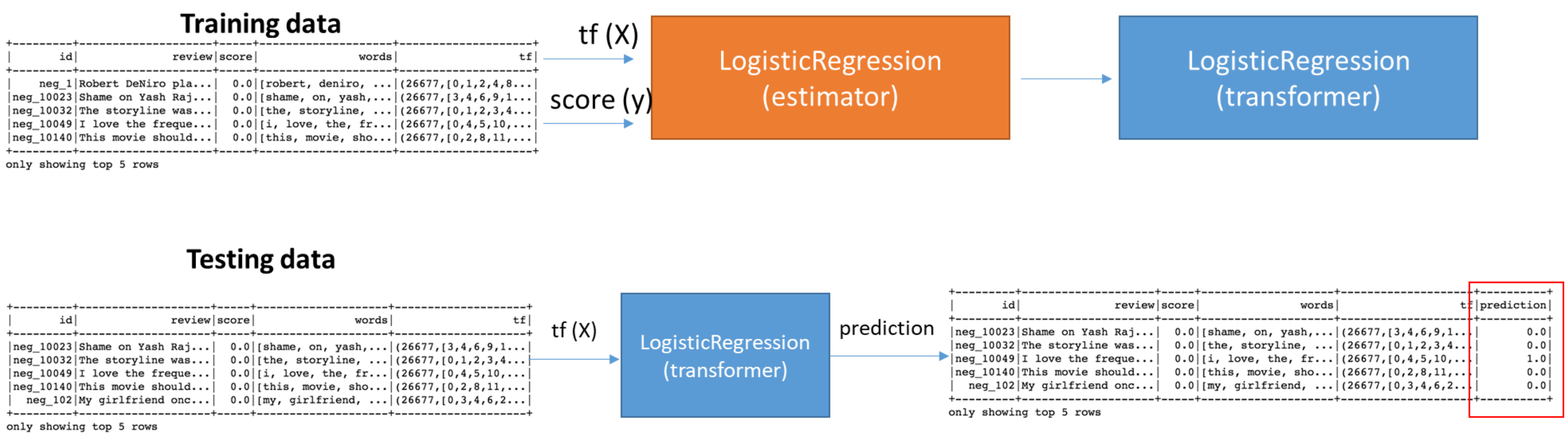
doc_id	text	user_id
1	cats are cute	0
2	dogs are playfull	0
3	lions are big	1
4	cars are fast	1



doc_id	text	user_id	words	features
1	cats are cute	0	[cats, are, cute]	(9,[0,3,5],[1.0,1.0,1.0])
2	dogs are playfull	0	[dogs, are, playfull]	(9,[0,2,7],[1.0,1.0,1.0])
3	lions are big	1	[lions, are, big]	(9,[0,1,6],[1.0,1.0,1.0])
4	cars are fast	1	[cars, are, fast]	(9,[0,4,8],[1.0,1.0,1.0])

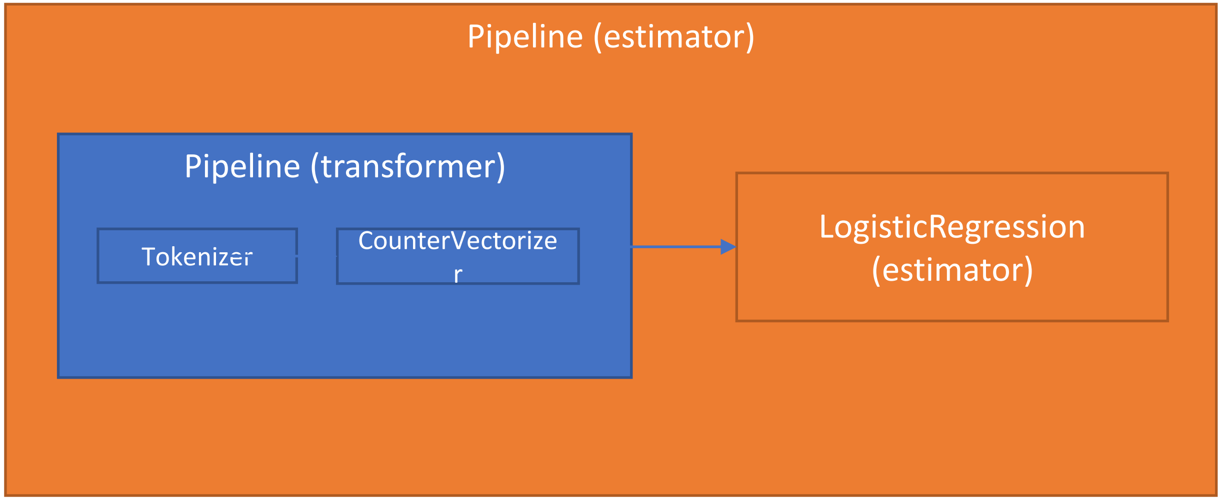
Spark ML: Algorithms

- Some Estimators are algorithms that work on DataFrames
- In this context, an algorithm is a machine learning model
- For example, LogisticRegression



Spark ML: Algorithms

- Algorithms can be part of Pipelines
- Pipelines can be combined with other Pipelines



Evaluators

- An evaluator allows us to see how a given model performs according to specified criteria
- An evaluator is used to select the best model from a group of models.
- An evaluator compares model predictions to truth data and calculates a score indicating how well the model performed.

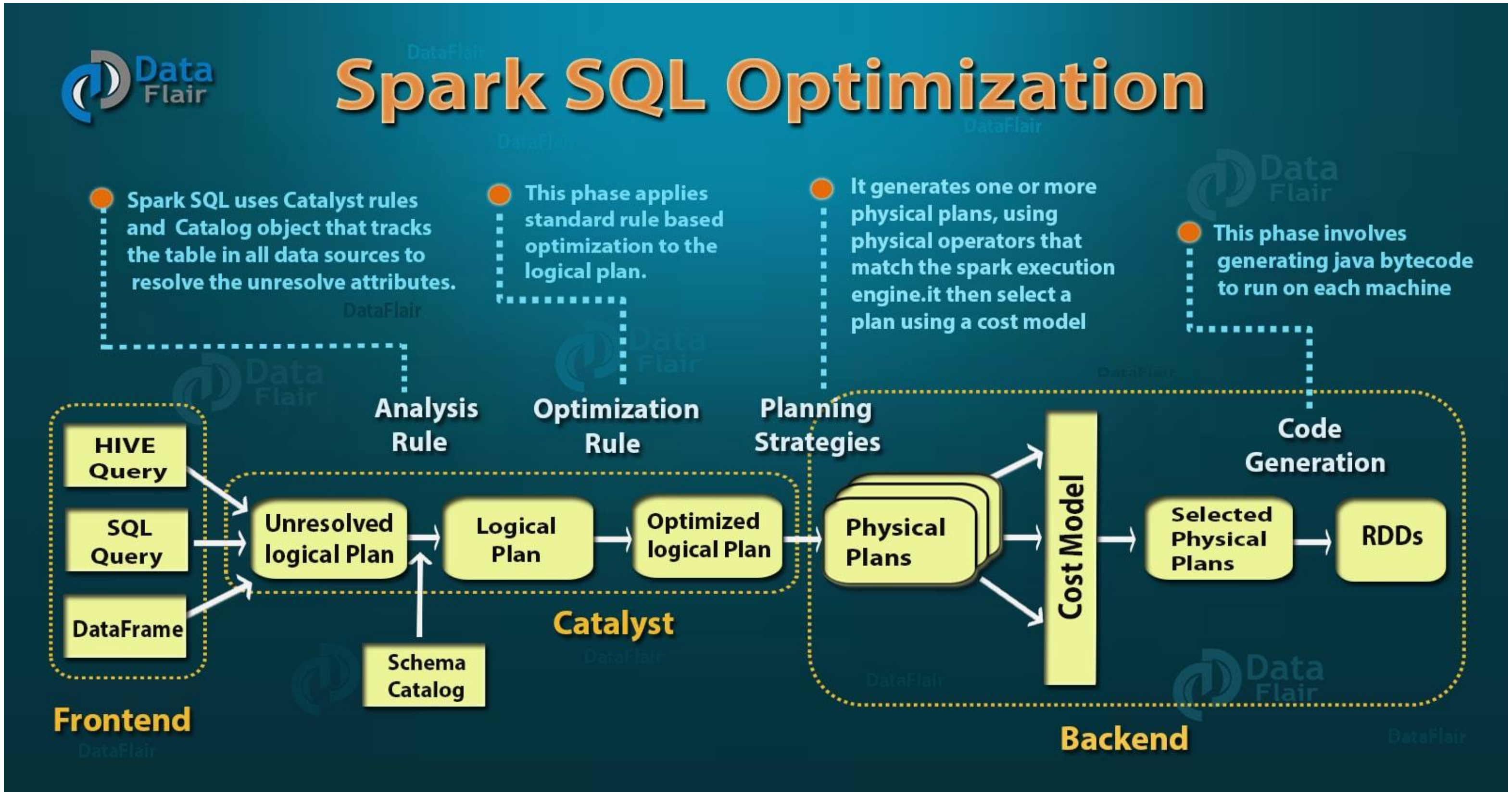
Summary (1 of 2)

- ***Apache Spark*** is a fast, in-memory computing system that runs on Hadoop.
- An application in Spark has several main components, including a driver program, worker nodes, executors and tasks.
- The **SparkContext** object is a key component of the driver program.
- An RDD is a fault-tolerant collection of elements that can be operated on in parallel.
- There are several ways to create an RDD in Spark: the **parallelize** function or a reference to a file in HDFS. **textFile sequenceFile**
- There are two types of operations that can be done on RDDs: ***transformations*** and ***actions***.

Summary (2 of 2)

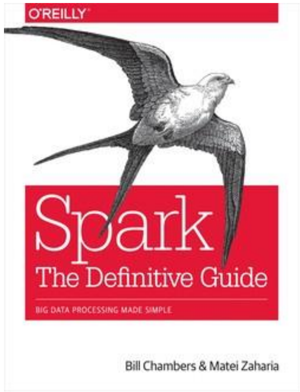
- ***MLlib*** is a Spark implementation of some common machine learning algorithms and utilities.
- MLlib contains **algorithms** for classification, regression, clustering and recommendation.
- **Transformers** convert raw data in some way
- **Estimators** need to learn something from the data in order to transform the data
- **Pipelines** are a collection of transformers and estimators
- Algorithms are

Spark Sql



Data Flair
Spark SQL Optimization
Spark SQL uses Catalyst rules and Catalog object that tracks the table in all data sources to resolve the unresolve attributes.
This phase applies standard rule based optimization to the logical plan.
It generates one or more physical plans, using physical operators that match the spark execution engine.it then select a plan using a cost model
This phase involves generating java bytecode to run on each machine
Analysis Rule
Optimization Rule
Planning Strategies
Code Generation
HIVE Query
SQL Query
DataFrame
Unresolved logical Plan
Logical Plan
Optimized logical Plan
Physical Plans
Cost Model
Selected Physical Plans
RDDs
Schema Catalog
Catalyst
Frontend
Backend

References



https://www.oreilly.com/library/view/spark-the-definitive/9781491912201/

https://databricks.com/blog/2016/07/14/a-tale-of-three-apache-spark-apis-rdds-dataframes-and-datasets.html

https://data-flair.training/blogs/apache-spark-rdd-vs-dataframe-vs-dataset/

http://www.jamesserra.com/archive/2017/12/is-the-traditional-data-warehouse-dead/